

A Supervised Generative Encoder-Based Approach to Improve Test Case Prioritization in Web Applications

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Abstract—An advanced software systems have to accomplish a huge set of necessities because of their durability and complexity. Accordingly, the essential stage of software testing in a software engineering project with respective program behavior to its requirements is evaluated. Regression testing is the process of retesting the software system after variations have arisen, for example, after a new form is emerged. Generally, only the subset of test conditions are performed for a specific version as a result of limited resources. To decrease these problems, one of the method is to assume test case prioritization (TCP) while many works has specified that TCP enhance an overall performance of software testing. TCP hold numerous types of models, which contains own weaknesses and strengths. Many studies have shown an attention in the application of machine learning in TCP recently. This study presents a Leveraging Artificial Intelligence for Enhancing the Effectiveness of Test Case Prioritization Techniques (LAI-ETCPT) in Web Application Testing. The main objective of the LAI-ETCPT technique is to significantly enhance software testing efficiency by effectively prioritizing critical test cases. In the data preprocessing stage, the LAI-ETCPT method handles missing values and uses a normalization technique to ensure high-quality input data for further processing. For dimensionality reduction, a hybrid approach combining minimum redundancy maximum relevance and recursive feature elimination is employed to recognize the most informative features. In the classification process, a supervised variational autoencoder is applied to capture complex relationships and generate meaningful representations of test cases. To ensure an improved performance of LAI-ETCPT model, a comprehensive simulation analysis is conducted, and the results demonstrate the improvement of the LAI-ETCPT technique over recent methods.

Keywords— *Test Case Prioritization; Software Testing; Minimum Redundancy Maximum Relevance; Supervised Variational Autoencoder; Machine Learning*

I. INTRODUCTION

Software engineering is not objective about software development and programming. Software engineering itself is an application of engineering measures in the expansion of any software in a systematic manner [1]. By using the process of

software development, the software testing takes an extended time for performance and also more expensive stage. Software testing itself has been generally executed repeatedly, even under time limits and stable resources. The groups of software engineering are often assured to end their testing activities due to time and financial needs that is caused the complications like issues with software quality and customer agreements. Regression testing is an action that can be confirmed that new varieties do not affect the previous software functions. Since the software develops, the software test set takes the trends to improve in size that is often created it as higher cost for implementation. Research exhibits that regression testing is a costly method that can need about higher than 33% of the collective expenditures of the software [2]. While software systems rise in difficulty and size, the demand for efficient test case prioritization (TCP) has become more obvious. TCP includes deciding which test cases must be performed to exploit testing effectiveness and efficiency [3]. Proper prioritization assists teams in focusing on the most crucial parts of the application, ensures that huge risk features are verified initially, and that resources are assigned effectively. TCP intends to collect test cases to attain timely optimization depending on desired properties [4]. It offers the proficiency to accomplish initial test cases that are extremely significant, along with certain measures, and produce the preferred result, like exposing problems earlier and providing comments to the testers [5]. TCP also assists in finding the ideal permutation of a sequence of test cases and could be performed correspondingly. TCP methods are categorized into two sets: model-driven and code-driven methods [6]. The model-driven TCP methods utilize the method, which demonstrates the preferred behaviour of the system, to prioritize test cases. The code-driven TCP methods utilize the application source code to prioritize test cases. The emergence of Artificial Intelligence (AI) has developed various aspects of software testing, especially in TCP [7]. AI-based automation utilizes data analytics and machine learning (ML) methods to improve the efficacy and precision of testing processes [8]. ML can examine big databases rapidly, allowing fast TCP. Likewise, ML methods can classify patterns and correlations that can be lost by human testers, resulting in more consistent forecasts.

Recently, ML approaches have been accepted by TCP [9]. As software systems become complicated, certain traditional TCP methods can't scale well. This increasing difficulty has solidified the demand for ML approaches in TCP. Furthermore, Deep Learning (DL), as a subdivision of ML, improves TCP, providing an information-based and automatic solution to enhance software quality testing effectiveness and efficacy [10].

This paper presents a Leveraging Artificial Intelligence for Enhancing the Effectiveness of Test Case Prioritization Techniques (LAI-ETCPT) in Web Application Testing to greatly improve software testing efficacy by prioritizing crucial test cases. In the data preprocessing phase, the LAI-ETCPT methodology handles missing values and employs a normalization method to guarantee high-quality data for further processing. For feature reduction, a hybrid model combining minimum redundancy maximum relevance (MRMR) and recursive feature elimination (RFE) is utilized for identifying the most beneficial features. In the classification process, a supervised variational autoencoder (SVAE) is employed for capturing intricate relationships and generate meaningful representations of test cases. To guarantee an enhanced performance of LAI-ETCPT approach, a broad simulation analysis is executed, and the outcomes prove the improvement of the LAI-ETCPT model over current models.

II. REVIEW OF LITERATURE WORKS

In this section, a brief literature review on the TCP model is presented. Singh et al. [11] presented the Support-driven Whale Optimization Algorithm (SWOA) and test case reduction for dispersed agile software development employing regression testing. This research aims to explore regression testing approaches in agile advanced teams and to learn the optimal cluster test cases. The presented approach is split into 2 phases: selection and prioritization are performed when the test cases have been grouped and retrieved. The clustering test cases are prioritized and sorted in this phase for ensuring that the very crucial moments are selected initially. Su et al. [12] introduced a new Attention Transfer RL for TCP (ATRL-TCP) technique. This approach utilizes the intensity of historical data and error rates to help the test cases. This approach enables the shifting concentration depending on the information features. This causes the method's incapability to manage several ranking circumstances in Continuous Integration (CI). Chen et al. [13] proposed an innovative deep RL-driven structure for automated test cases creation in hardware validation. This method integrates conventional methods of verification with developed DL methods for improving security susceptibility detection and test coverage. The structure integrates an adapted Deep Q-Network method with preferred experience replay, combined with dynamic mutation and static analysis strategies. The method uses a complete reward system that reflects many coverage metrics.

Mamata et al. [14] examined utilizing the advantage of transfer learning for TCP. In some instances, model-driven transfer learning is an efficient solution for sharing knowledge

between various projects without exposing information to other investors. Therefore, the efficiency of ML for TCP can be reduced for a minimal amount of information and a lower failure rate, while employing present information with analogous patterns from other fields may be useful. In [15], a TCP approach that depends on a genetic and RL method is presented. The traditional genetic method of starting population and selection processes is enhanced by integrating an ant colony technique to select a part of the early population in the genetic method. The enhanced technique is related to testing the cloud-network convergence environment, and the optimization-seeking capabilities of the RL-driven ant colony genetic technique, the ant colony genetic technique, and the traditional genetic method are analyzed and compared. Tiutin and Vescan [16] introduced a TCP that depends upon NN Classification (TCP-NNC) method for advancing the TCP strategies. This method integrates with other factors, the relations among necessities, tests, and discovering faults, depending on which an ANN is trained to predict significances for novel test cases.

III. MATERIALS AND METHODS

In this manuscript, we have proposed an LAI-ETCPT in Web Application Testing to enhance software testing effectiveness by precisely prioritizing critical test cases. The process begins with data preprocessing to ensure clean and consistent input. Next, feature selection approaches such as MRMR and RFE identify significant features for TCP. The selected features are then passed to the SVAE model for classification.

A. Data Preprocessing

In this step, the proposed model handles missing values and uses a normalization technique to ensure the data is of high-quality for further processing. In this proposed model, data are gathered from datasets and they are assumed to the phase of data preparation [17]. The raw dataset may contain noise, categorical attributes, and missing values that can affect classification performance. The data pre-processing segment alters every data evenly into numerical values. After this procedure, an accurate and compact database is attained from which an input is assumed to FS and classification techniques for effectual classification and normal data. From the assumed databases, data normalization is executed to minimize the redundant data and attain improved input data. The proposed model uses Min-Max normalization for scaling the data with the ranging from 0 to 1. The formulation that calculates the standardized values utilizing Min-Max normalization has been provided in Eq. (1).

$$V' = \frac{V - \text{Min } F}{\text{Max } F - \text{Min } F} \quad (1)$$

V' represents normalized value; V means a feature value. By regularizing, the accuracy is enhanced, thereby it improves an accuracy of the model.

B. Feature Selection Techniques

In this stage, a hybrid methodology combining MRMR and RFE is used to identify the most crucial features. To choose the

most logical features and extracting the undesired features, FS reduces the feature counts in a feature collection [18]. Both the MRMR and RFE method of FS are effectual in this recommended approach. MRMR employs the conditions named minimal redundancy (\min_D) and the maximum relevance (\max_R).

$$\max_R = \frac{1}{|f|} \sum_{j \in f} m(i, j) \quad (2)$$

$$\min_D = \frac{1}{|f|^2} \sum_{i, j \in f} m(i, j) \quad (3)$$

Now $m(x, y)$ represents mutual information and f represents the set of features.

$$m(x, y) = \iint q(x, y) \log \frac{q(x, y)}{q(x)q(y)} dx dy \quad (4)$$

In Eq. (5), RFE effectually acquires the finest subset of ideal features.

$$\max Q(D, R); Q = D - R \quad (5)$$

C. Classification using SVAE Approach

In this section, SVAE is deployed as a classification model to obtain complex relationships and form meaningful representations of test cases. The traditional approach for contextualizing their limitations, accomplished by a complete exposition of the proposed SVAE framework [19]. Conventional models take linear relations between variables. These linear approaches are computational effective and frequently offer interpretability outcomes. On the other hand, their linear assumptions considerably make their flexibility, creating them inadequate to capture the intricate, non-linear relations. To solve this crucial restriction, the propose an innovative SVAE, a deep generative technique integrating non-linear representation learning with a supervised classification model. The SVAE explicit objective to address the inadequacies of linear methods to obtain difficult interactions within higher-dimensional information and efficiently managing mixed data types. These processed inputs are concatenating into a combined representation into a multilayer neural network encoding. This encoding network process parameter ($\mu, \log\sigma^2$) describing a latent Gaussian distribution. The parameter z is the Latent variables for sample employing the reparametrized approach:

$$z = \mu + \sigma \odot \epsilon, \epsilon \sim \mathcal{N}(0, I) \quad (6)$$

Also, it enables an effective stochastic gradient descent training whereas protecting differentiable.

Afterward, a decoding network rebuilds the numerical portion of input features from latent variables, assuring that the hidden representation protects crucial data about the actual network structure. Alongside, a supervised classifier head is directly mapped these hidden representations to the class labels, incorporating the predictable supervision into the training method. Consequently, the SVAE objective concurrently decreases the reconstructive error, classification error, and a regularization term in accordance with the Kullback–Leibler (KL) divergence:

$$\mathcal{L}_{total} = \mathbb{E}_{q_\phi(z|x)} \left[\left\| \hat{X}_{num} - X_{num} \right\|^2 \right] + \alpha (\hat{y} - y)^2 + \beta D_{KL}(q_\phi(z|x) \| p(z)) \quad (7)$$

Here, the parameter α and β are controlled the stability among supervised classification efficiency and latent space regularization. The KL divergence executes as a probabilistic regularizes and avoid the overfitting, thus it assures the structured, various explainable latent.

IV. EXPERIMENTAL EVALUATION

In this section, the performance analysis of LAI-ETCPT approach is inspected under Test case Prioritization dataset [20]. This dataset contains 59192 samples under dual classes as shown below in Table 1. The total no. of features are 8 but only 7 are chosen.

TABLE I
DETAILS OF DATASET

| Classes of Verdict | Samples |
|--------------------|--------------|
| Test Case Fail (1) | 12642 |
| Test Case Pass (0) | 46550 |
| Total | 59192 |

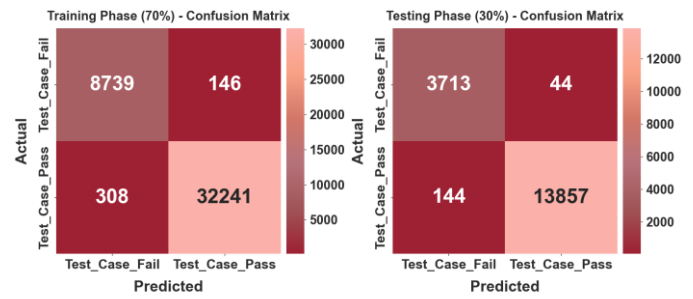


Fig. 1. Confusion matrices of (a, b) 70% and 30%

Fig. 1 reveals the confusion matrices with accurate classification of every classes under 70:30. The results indicate that the LAI-ETCPT approach has effectual recognition of the fail and pass samples under 2 classes.

Table 2 signifies a classifier solution of LAI-ETCPT technique under 70:30. On 70% TRPHE, the proposed LAI-ETCPT methodology gains an average $accu_r$, $preci_n$, $recal_l$, $F1_{Score}$, and $G_{Measure}$ of 98.71%, 98.07%, 98.71%, 98.38%, and 98.39%, correspondingly. Furthermore, on 30% TSPHE, the proposed LAI-ETCPT approach attains an average $accu_r$, $preci_n$, $recal_l$, $F1_{Score}$, and $G_{Measure}$ of 98.90%, 97.98%, 98.90%, 98.43%, and 98.43%, correspondingly.

TABLE II
CLASSIFIER OUTCOME OF LAI-ETCPT MODEL UNDER 70:30

| Class Labels | $Accu_r$ | $Prece_n$ | $Recal_l$ | $F1_{Score}$ | $G_{Measure}$ |
|--------------|----------|-----------|-----------|--------------|---------------|
| TRPHE (70%) | | | | | |

| | | | | | |
|--------------------|--------------|--------------|--------------|--------------|--------------|
| Test_Case_Fail | 98.36 | 96.60 | 98.36 | 97.47 | 97.47 |
| Test_Case_Pass | 99.05 | 99.55 | 99.05 | 99.30 | 99.30 |
| Average | 98.71 | 98.07 | 98.71 | 98.38 | 98.39 |
| TSPHE (30%) | | | | | |
| Test_Case_Fail | 98.83 | 96.27 | 98.83 | 97.53 | 97.54 |
| Test_Case_Pass | 98.97 | 99.68 | 98.97 | 99.33 | 99.33 |
| Average | 98.90 | 97.98 | 98.90 | 98.43 | 98.43 |

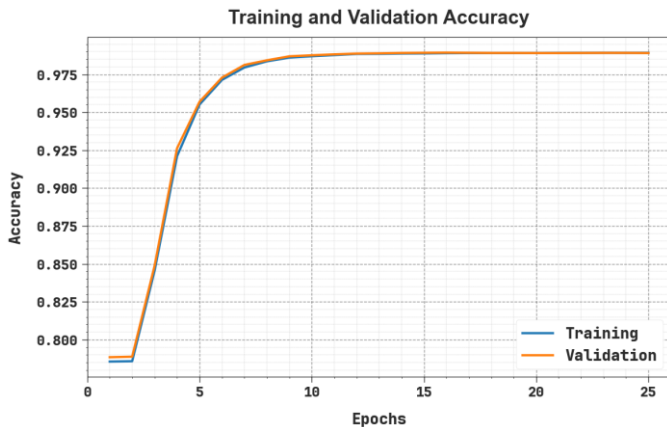


Fig. 2. Accuracy curve of LAI-ETCPT model

Fig. 2 exhibits the training (TRAN) and validation (VALD) accuracy of LAI-ETCPT method over 25 epochs. Both curves progressively rise and slowly converging, which signifies that the model is learning effectually. The VALD accuracy constantly stays slightly greater than the TRAN accuracy, representing that the model is not overfitting and is generalizing well to unseen data. The fluctuations in accuracy are expected owing to the intricacy of the task, but the entire upward tendency establishes enhanced outcome and steadiness of the model.

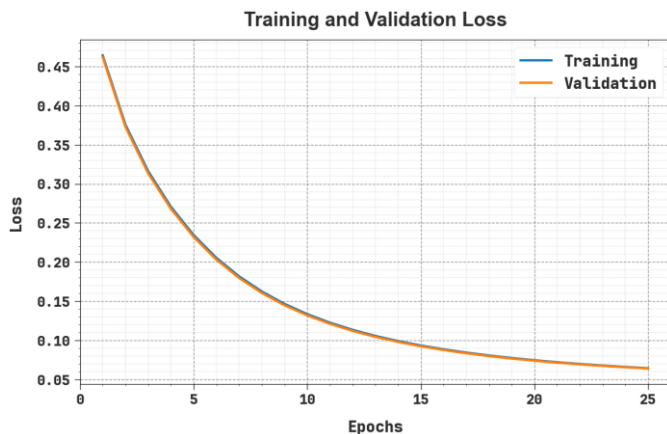


Fig. 3. Loss curve of LAI-ETCPT model

Fig. 3 demonstrates the TRAN and VALD loss of LAI-ETCPT method over 25 epochs. Both curves reveals a constant

downward tendency, signifying that the model is effectually lessening error during learning. The VALD loss remains slightly lesser than the training loss through most epochs, recommending better generality and no signs of overfitting. However, some fluctuations are identified to become gradually reliable and stable.

Table 3 portrays the comparative study of LAI-ETCPT technique with existing approaches under several metrics [21]. The table value implies that the LAI-ETCPT method has exhibited effective performances. Depend on $accur_y$, the LAI-ETCPT methodology has attained maximal $accur_y$ of 98.90% although the CART, Random Forest, SVM, Logistic Regression, NB, KNN, and J48 Decision Tree methods have got minimal $accur_y$ of 87.03%, 85.97%, 84.50%, 84.45%, 85.70%, 83.05%, and 84.05%, correspondingly. Moreover, depend on $preci_n$, the LAI-ETCPT model has achieved greater $preci_n$ of 97.98% however the CART, Random Forest, SVM, Logistic Regression, NB, KNN, and J48 Decision Tree techniques have got lower $preci_n$ of 87.31%, 91.14%, 84.46%, 93.70%, 80.87%, 93.06%, and 89.79%, correspondingly. Meanwhile, depend on $recal_l$, the LAI-ETCPT methodology has gained superior $recal_l$ of 98.90% although the CART, Random Forest, SVM, Logistic Regression, NB, KNN, and J48 Decision Tree systems have got lower $recal_l$ of 88.54%, 81.62%, 89.22%, 97.18%, 87.48%, 83.26%, and 93.59%, correspondingly. Likewise, depend on $F1_{score}$, the LAI-ETCPT technique has attained maximum $F1_{score}$ of 98.43% whereas the CNN-LSTM, KNN, DML-SVM, Hybrid sensor system, Kaze Features, EJH-CNN-BiLSTM, and SFCM-DenseNet-ELM techniques have accomplished minimum $F1_{score}$ of 87.93%, 86.12%, 84.31%, 95.13%, 97.85%, 82.93%, and 91.43%, respectively. Therefore, the proposed LAI-ETCPT technique is highly effective when compared to other existing technique from this detailed comparative analysis.

TABLE III
COMPARATIVE ANALYSIS OF LAI-ETCPT METHOD WITH EXISTING APPROACHES

| Methods | $Accur_y$ | $Preci_n$ | $Recal_l$ | $F1_{Score}$ |
|---------------------|-----------|-----------|-----------|--------------|
| CART Model | 87.03 | 87.31 | 88.54 | 87.93 |
| Random Forest | 85.97 | 91.14 | 81.62 | 86.12 |
| SVM Classifier | 84.50 | 84.46 | 89.22 | 84.31 |
| Logistic Regression | 84.45 | 93.70 | 97.18 | 95.13 |
| Naïve Bayes | 85.70 | 80.87 | 87.48 | 97.85 |
| k-Nearest Neighbor | 83.05 | 93.06 | 83.26 | 82.93 |
| J48 Decision Tree | 84.05 | 89.79 | 93.59 | 91.43 |
| LAI-ETCPT | 98.90 | 97.98 | 98.90 | 98.43 |

V. CONCLUSION

In this article, we have presented an LAI-ETCPT in Web Application Testing for significantly enhancing software testing effectiveness by accurately prioritizing critical test cases. In the data preprocessing step, the LAI-ETCPT technique handles missing values and utilized a normalization method to confirm high-quality input data for further processing. For dimensionality reduction, a hybrid method combining MMRM and RFE is used to recognize the most crucial features. In the classification process, a SVAE is deployed to obtain complex relationships and form meaningful representations of test cases. To confirm the enhanced performance of the LAI-ETCPT system, a comprehensive simulation investigation is conducted, and the results indicate an improvement of the proposed LAI-ETCPT approach over recent methods.

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